Combining system and user belief on classification using the DSmT combination rule

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Abstract – Having a correct and timely classification solution for objects has become increasingly important as well as increasingly difficult to obtain in new maritime military missions; a decision support system is therefore needed. In decision support systems a challenge lies in how operator and system belief can be reconciled. This paper presents a support system for the classification process using Dezert-Smarandache theory (DSmT) for information fusion. This system is implemented to test these concepts in practise. With this implementation we show that our methodology provides the operator with various levels of interaction with the system. The interface also shows the belief state of the system at any given time, increasing operator trust in the system.

Keywords: Classification, Dezert-Smarandache Theory, Human-Computer Interaction, Reasoning with uncertainty.

1 Introduction

The classification process aboard naval warships is becoming more and more complex, due to three main factors. Missions now are typically executed in more challenging geographical locations where rapidly changing environmental conditions make sensor performance harder to predict and enable hostile forces to stay hidden longer. Thus, the reaction time is diminished.

Furthermore, today's missions are characterised by asynchronous threats and missions draw more media attention. The first makes classification itself harder whereas the latter results in high pressure not to make mistakes, see [1].

The last factor refers to developments contradictory in impact: sensor systems are becoming increasingly complex, requiring increasing technical knowledge levels of the operators to optimally deploy the available sensors. On the other hand there is a strive to reduce the ship's complements and to reduce the training time for operators due to budget cuts.

Deploying sensors optimally is important for the classification process. Sensors can reduce the amount of uncertainty in the compiled picture, thus the input of the classification process is correct and accurate. When sensors are not deployed in an optimal fashion, much uncertainty occurs on the input of the classification process, reducing classification accuracy.

Intelligent classification support can alleviate these problems. This paper focuses on the required cooperation mechanism between operator and system when automated classification is possible. In section two we will start with the background of this research, which is part of a larger ongoing research program. As an information combination methodology we choose to use Dezert-Smarandache theory (DSmT), which is briefly discussed in section three. How this theory can be applied in the field of classification in military command and control systems is discussed in section four. Section five explains how the operator can exert influence in the resulting classification system using DSmT. The implementation of this system is discussed in section six. Finally, sections seven and eight discuss future work and the conclusions of this research.

2 Background

The research presented in this paper is conducted as a part of the ongoing STATOR[1] project: a collaboration between the Royal Netherlands Navy, the International Research Centre for Telecommunication and Radar of the Delft University of Technology and Thales the Netherlands. Focus of this project was the management of sensor suites on single or multiple platforms and fusion of the data provided by these sensors. The goal is to develop a decision support system where the operator can communicate with the sensor suite(s) as a whole in operational parameters without the need for technical knowledge. The overall concept used for this is discussed in [2]. We want to manage the whole suite because sensors can give similar and/or complementary data. Exploiting this, means that the sensor suite should be considered as a whole by the sensor manager.

2.1 Sensor Management

Previous research shows that sensor management seeks to compile and maintain a picture of the environment that is

[1] STATOR: Sensor Tuning And Timing on Object Request

complete and accurate, [3]. In [4] a three-stage sensor manager is introduced based on this notion. The first stage determines the sensor task that needs to be executed in order to reduce the maximum amount of uncertainty in the compiled picture. Since the uncertainty in classification can be reduced in various ways, [5], and because this uncertainty reduction is important in achieving situation awareness, it seems logical to look at the classification process within the broader study into sensor management. More information about the three-stage sensor manager can be found in [2].

2.2 Classification

Having a *good* and *timely* classification solution is of vital importance to mission success in many fields. Before this can be done however, we need to describe:

1) what classification is;
2) what a *good* classification solution is; and
3) what a *timely* solution is.

The answer to the first question is described in section four, but in short: classification tries to recognise the observed object with as much detail as possible, e.g. recognising that a surface contact is the HNLMS[2] Tromp of the Dutch Air Defence and Command frigate class.
A *good* classification is the solution where a sufficient amount of detail is obtained. E.g., the distinction between two types of sea skimming missiles causes only a little reduction in risk uncertainty: both will most likely destroy the ship so risk-wise they are equal. Distinguishing between an airliner and a fighter however, does reduce risk uncertainty because the first is considered less threatening than the latter. The definition of risk that we use and how it is calculated can be found in [6]. Besides the advantage of reducing the uncertainty in the risk posed by an object, a good classification also improves radar performance in tracking, as shown in [7].
In the military field, the starting point is to assume the worst-case scenario. For incoming objects this means that, at a certain point in time, precautionary actions must be taken. Before this happens, a classification solution could negate the necessity of actions thus preventing collateral damage. A *timely* solution is therefore the solution that reduces enough class uncertainty for deciding on appropriate actions.
In the classification process we search for a good and timely solution. This search space needs to be modelled in order to use automated classification techniques. This model should facilitate the requirements needed to find correct and timely solutions: the model needs to facilitate specific as well as more generic solutions. In section four we will discuss how the search space in the field of classification space is modelled.

2.3 Interaction with the operator

Operational command and control systems in use with the Royal Netherlands Navy rely on operator input, especially the classification process. However, new types of missions require more support for the classification process during missions. This does not mean that the operator cannot classify: the operator should always be enabled to give the classification solution.
It is known that operators are not always best suited to solve complex problems in time. We therefore want to explore the possibility of more cooperation between the system and the operator, where each is responsible for the task they are best suited for. The operator makes tactical decisions and gives operational information relevant to the mission whereas the system can perform computations to solve the more technical problems. When cooperating, the operator needs to be able to trust the system. In order to earn operator trust, the system must be able to communicate its belief state and be able to explain its actions. The result is an architecture where the systems beliefs are combined with the users belief in order to find good and timely solutions.

3 DSmT combination rule

Dezert and Smarandache introduced a theory on combining paradoxical, uncertain, and imprecise information from various sources in [8] and this theory has led to many implementations as can be seen e.g. in [9]. This theory is denoted as DSmT, which we will shortly discuss in this section. For more information on this theory the reader is referred to the aforementioned references [8] and [9]. We then continue with the Proportional Conflict Redistribution rule (PCR5[3]), [10] and [11].

3.1 General DSmT

In this section we will briefly discuss the basic concepts of DSmT that we use in the field of classification, namely the basic model, the belief function and the different combination rules.

3.1.1 The model

Let $\Theta = \{\theta_1, \theta_2, ..., \theta_n\}$ be the frame of discernment with exhaustive elements θ_i. (Note that they are not exclusive as is the case in Dempster-Shafer theory.) This model is called free when no assumptions are made about the hypotheses θ_i except for the exhaustiveness.

[2] HNLMS: Her Netherlands Majesty; The prefix for all ships of the Royal Netherlands Navy.

[3] In [10] all PCR-rules are described; we however will only discuss and use PCR5.

Of course, this model does not fit real-life problems since some combinations of hypotheses are time dependent or are not valid anymore when more knowledge becomes available. A hybrid model, denoted *M*, can be constructed to deal with these integrity constraints.
When the integrity constraints state that all overlapping hypotheses are invalid, the model used for Shafer's rule of combination is obtained.
The cornerstone of DSmT is the free Dedekind lattice denoted in DSmT as the *hyper-power set*. This hyper-power set D^{Θ} is defined as the set of all composite propositions built from elements of Θ with $\cup$ and $\cap$ operators such that:

1. $\emptyset, \theta_1, \theta_2, ..., \theta_n \in D^{\Theta}$;
2. If $A, B \in D^{\Theta}$ then $A \cup B \in D^{\Theta}$ and $A \cap B \in D^{\Theta}$;
3. No other elements belong to D^{Θ} except those obtained using rules 1 and 2.

The cardinality of the hyper-power set for $n \geq 1$ follows the Dedekind sequence (i.e., 1, 2, 5, 19, 167, 7580, 7828353,...) as shown in [9]. Tombak et.al., describe the analytical form of this sequence in [12]. From the frame of discernment Θ a map is defined $m(.): D^{\Theta} \rightarrow [0,1]$:

$$m(\emptyset) = 0 \text{ and } \sum_{A \in D^{\Theta}} m(A) = 1 .$$

The quantity *m(A)* is called the generalised basic belief assignment (gbba) of *A*, also called the mass of *A*.

3.1.2 Combination rules in DSmT

The classic DSmT rule of combination holds when the model is free. When two independent sources give their belief masses according to $m_1(.)$ and $m_2(.)$ respectively, the combination rule for $\forall C \in D^{\Theta}$ is given in equation (1).

$$m_{12}(C) = \sum_{\substack{A,B \in D^{\Theta} \\ A \cap B = C}} m_1(A) \cdot m_2(B) \qquad (1)$$

When the classic rule of combination is used in real-life fusion problems so-called integrity constraints must be taken into account to impose assumptions about the model. In such cases, the hybrid rule of combination for *k* independent sources with belief assignments $m_1(.),...,m_k(.)$ is defined for $\forall A \in D^{\Theta}$ by equation 2.

$$m(A) = \phi(A) \cdot [S_1(A) + S_2(A) + S_3(A)] \qquad (2)$$

In equation (2) all sets are in the canonical form and $\phi(A)$ is the characteristic non-emptiness function of a set *A*, i.e. $\phi(A)$=1 if $A \notin \emptyset$ and $\phi(A)$= 0 otherwise, where $\emptyset = \{\emptyset, \emptyset_M\}$. $\emptyset_M$ is the set of all elements of D^{Θ} which have been forced to be empty through the constraints of the model *M* and $\emptyset$ is the classical empty set. In equation (2) the following is defined:

$$\begin{cases} S_1(A) = \sum\limits_{\substack{X_1, X_2, ..., X_k \in D^{\Theta} \\ X_1 \cap X_2 \cap .. \cap X_k = A}} \prod\limits_{i=1}^{k} m_i(X_i) & ; \\ S_2(A) = \sum\limits_{\substack{X_1, X_2, ..., X_k \in \emptyset \\ [U=A] \vee [(U \in \emptyset) \wedge (A = I_t)]}} \prod\limits_{i=1}^{k} m_i(X_i) & ; \\ S_3(A) = \sum\limits_{\substack{X_1, X_2, ..., X_k \in D^{\Theta} \\ X_1 \cup X_2 \cup .. \cup X_k = A \\ X_1 \cap X_2 \cap .. \cap X_k \in \emptyset}} \prod\limits_{i=1}^{k} m_i(X_i) & ; \end{cases}$$

with $U = u(X_1) \cup u(X_2) \cup ... \cup u(X_k)$ where $u(X)$ is the union of all θ_i that compose *X*. and I_t is the union of all elements in Θ, in other words: total ignorance.

3.2 PCR5

The general idea behind the PCR5 rule is to transfer conflicting masses to the non-empty elements that are involved in the conflict as opposed to transfer it to relative ignorance, which is the case in hybrid DSmT. The various PCR rules can be found in [10], and the PCR5 rule, which we use, is also discussed in [11]. We use example 1 – taken from the aforementioned references – to illustrate this principle. In this example, the combination rule for two sources is used. The combination rule for more than two sources can be found in [10].

Example 1
Let the frame of discernment be $\Theta = \{A, B\}$. Two experts have given their opinion as follows: $m_1(A)$ = 0.6, $m_1(A \cup B)$ = 0.4, $m_2(B)$ = 0.4 and $m_2(A \cup B)$ = 0.7. Combining these using equation (1) produces Table 1.
When assuming Shafer's model of exclusiveness the conflicting mass is $m_{12}{}^{f}(A \cap B) = 0.18$. When using the hybrid rule of combination this conflicting mass would be transferred to $m_{12}(A \cup B)$: the relative ignorance.

Table 1 Generalised basic belief assignments of two experts combined using classic DSmT.

	A	B	$A \cup B$	$A \cap B$
$m_1(.)$	0.6	0	0.4	0
$m_2(.)$	0	0.3	0.7	0
$m_{12}{}^f(.)$	0.42	0.12	0.28	0.18

In PCR5, the conflicting mass is transferred to the elements involved in the conflicting mass. Since $m_{12}{}^f(A \cap B) = m_1(A)m_2(B) + m_1(B)m_2(A)$, the only involved elements from D^Θ are A and B. The conflicting mass is therefore transferred to the masses of A and B proportional to the original masses of the sources that caused the conflict. The combined mass, $m_{12}{}^{PCR}(A)$ then becomes

$$m_{12}{}^{PCR}(A) = m_{12}{}^f(A) + \\ + \frac{m_1(A)}{m_1(A)+m_2(B)}(m_1(A)m_2(B)) + \\ + \frac{m_2(A)}{m_2(A)+m_1(B)}(m_2(A)m_1(B)) = 0.54$$

Similarly, $m_{12}{}^{PCR}(B) = 0.18$ and $m_{12}{}^{PCR}(A \cup B) = m_{12}{}^f(A \cup B)$ holds.

4 Using DSmT in classification

Most classifiers in military applications use classification trees, [13] and [14]. The problem with such an approach is that once the classifier gets stuck on a high level node it cannot classify further, although information is available to make a decision about a lower node. We therefore propose to use a more dynamic approach where 'branching' is done based on the available information. Or in other words, we define a search space where all possible objects are represented and the available information bounds the search space. Defining the search space like this means that elements in the search space are not necessarily exclusive, DSmT therefore seems a good mechanism to apply.

4.1 Classification model

Getting a good and timely classification of objects in the environment is essential for many mission-critical systems. Important in decision support systems that are to be utilised in this field is the combination of the terms *good* and *timely*. An exact solution is not as important as getting a suitable solution at the right time. For classification this means that the fast classification "helicopter" is preferred over a solution to provide distinction between an Apache and a Seahawk. Certain hierarchy in the classification space is therefore necessary, as well as a system that can operate on and switch between all hierarchical levels. Of course, the interdependencies between the different levels need to be defined: all elements on a certain hierarchical level are mapped to one or more elements at the next higher hierarchical level.

Since exclusiveness is not required in DSmT, we can apply its combination rules for a hierarchical structured classification space. For this domain we define three hierarchy levels: specific, generic and super classes. Belief can be assigned on any of the hierarchical level(s) and the combination mechanism based on DSmT can then combine beliefs as well as deal with conflicts.

The specific classes in the classification domain represent the different types of objects (e.g., an F16 or an Apache). The set of specific classes is defined as $C = \{\theta_1, \theta_2, ..., \theta_n\}$. This set consists of n exhaustive and exclusive elements.

The set of generic classes, $G = \{\gamma_1, \gamma_2, ..., \gamma_m\}$, consists of m exhaustive and exclusive elements. In this set, objects like 'fighter' and 'helicopter' are represented. Each element of G contains a subset of C.

Finally, the set of super classes, $S = \{\sigma_1, \sigma_2, ..., \sigma_k\}$, consists of k exhaustive elements. Each element from this set contains a subset of G. For the classification problem we consider all elements of C, G and S as the frame of discernment (Θ).

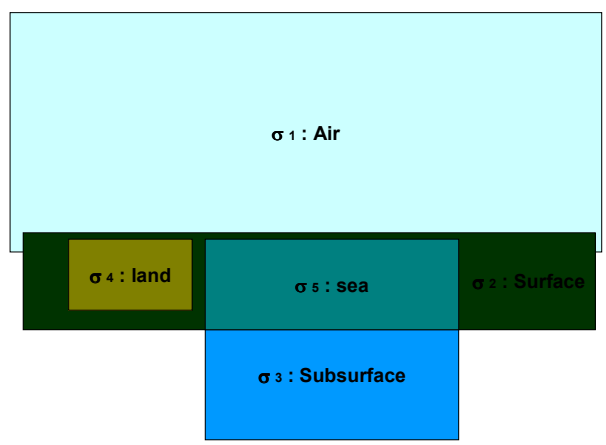

Figure 1 The different domains as represented as Venn diagram of S

Within the classification domain for military applications we define S using the different domains. This produces set S with five elements defined as the domains: σ_1 *air*, σ_2 *surface* and σ_3 *subsurface*. Furthermore, σ_4 and σ_5 represent the sub-domains *land* and *sea* of the surface class respectively. The Venn diagram of these five elements is given in Figure 1. Overlaps with the surface domain are included since both air and subsurface objects can operate in the surface domain, e.g. a surfaced submarine or low flying helicopter. Example 2 illustrates

how these hierarchical levels are used in the classification domain.

Example 2

Let C be given by:

θ_1:	Seahawk;	θ_6:	Apache;
θ_2:	F-16;	θ_7:	M-frigate;
θ_3:	Walrus-class;	θ_8:	K-class;
θ_4:	ADCF;	θ_9:	F-14;
θ_5:	Leopard II;	θ_{10}:	Boeing 747.

Let G be given by

κ_1:	Helicopter;	κ_4:	Frigate;
κ_2:	Fighter;	κ_5:	Tank;
κ_3:	Submarine;	κ_6:	Airliner.

For this example $\kappa_1 \cap C = \{\theta_1, \theta_6\}$, $\kappa_2 \cap C = \{\theta_2, \theta_9\}$, $\kappa_3 \cap C = \{\theta_3, \theta_8\}$, $\kappa_4 \cap C = \{\theta_4, \theta_7\}$, $\kappa_5 \cap C = \{\theta_5\}$ and $\kappa_6 \cap C = \{\theta_{10}\}$ holds. Two classifiers give information on their belief as given in Table 2 and Table 3. Assuming that the model is free, a large table needs to be constructed with all elements of D^{Θ}. In practise, we therefore do not want to work with a free model. Model constraints are introduced to reduce the amount of required calculations.

Table 2 The classification solution from source 1

A	$m_1(A)$	A	$m_1(A)$	A	$m_1(A)$	A	$m_1(A)$
θ_1	*0.150*	θ_6	*0.150*	κ_1	*0.250*	σ_1	*0.150*
θ_2	*0.005*	θ_7	*0.040*	κ_2	*0.002*	σ_2	*0.100*
θ_3	*0.000*	θ_8	*0.000*	κ_3	*0.000*	σ_3	*0.000*
θ_4	*0.036*	θ_9	*0.005*	κ_4	*0.041*	σ_4	*0.010*
θ_5	*0.009*	θ_{10}	*0.005*	κ_5	*0.005*	σ_5	*0.040*
				κ_6	*0.002*		

Table 3 The classification solution from source 2

A	$m_2(A)$	A	$m_2(A)$	A	$m_2(A)$	A	$m_2(A)$
θ_1	*0.075*	θ_6	*0.075*	κ_1	*0.175*	σ_1	*0.130*
θ_2	*0.010*	θ_7	*0.075*	κ_2	*0.002*	σ_2	*0.120*
θ_3	*0.020*	θ_8	*0.020*	κ_3	*0.010*	σ_3	*0.005*
θ_4	*0.075*	θ_9	*0.020*	κ_4	*0.100*	σ_4	*0.020*
θ_5	*0.010*	θ_{10}	*0.020*	κ_5	*0.010*	σ_5	*0.025*
				κ_6	*0.003*		

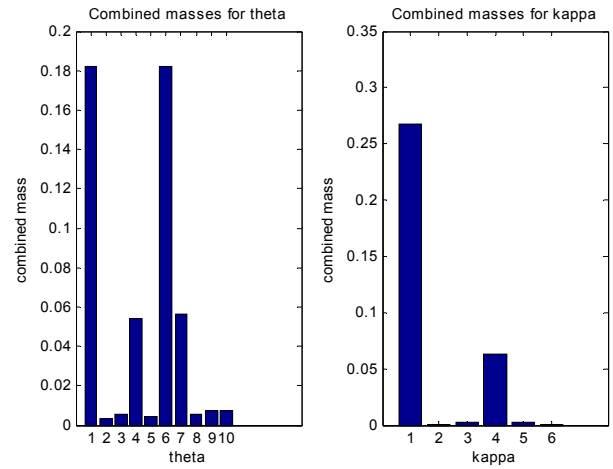

Figure 2 The histograms of the combined belief masses for *C* and *G* after applying PCR5 to resolve model constraints.

4.2 Model constraints

Due to the fact that *C* and *G* contain exclusive elements all the intersections of these elements in the hyper-power set can be constrained. Furthermore, due to the structure of *S* given in Figure 1 some intersections in the superclasses can be discarded as well. The PCR5 rule is used to redistribute all masses assigned to these intersections. We call the constraints that are made at this point, the model constraints since they are caused by the modelling of the classification space.

With PCR5 we have a well defined, 'easy' to implement solution to transfer all model constraints in example 2. This is straightforward because these constraints all deal with similar situations, as was the case in example 1, e.g. the model dictates that an object cannot belong to the air and the subsurface domains. The mass associated with that possibility is proportionally transferred to the air domain and the subsurface domain.

Using this combination scheme in example 2 to resolve the modelling conflicts we obtain the results shown in Figure 2 and Figure 3.

5 Interacting with the user

Imposing user constraints will be somewhat more complex than imposing model constraints, since more elements are involved. Looking at example 2, say that the operator imposes that the object is not a subsurface contact, $m(\sigma_3) \to 0$. The structure of the model then forces all masses assigned to the underlying elements of that domain to zero. The exception to this basic scheme is the surface domain: when set to zero all underlying elements that also belong to the air or the subsurface domain should not be set to zero due to the chosen modelling of the classification space, e.g. when an operator indicates that it is not a surface contact, the low flying helicopter should still be under consideration. Furthermore, the operator has the freedom to impose constraints on either *C*, *G* or *S*.

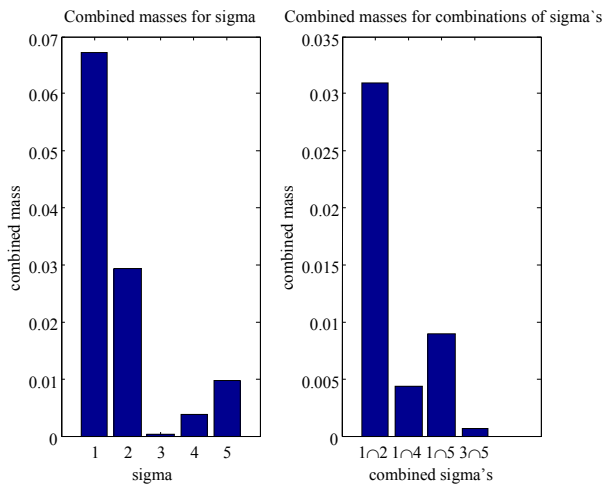

Figure 3 The histograms of the combined belief masses for *S* after applying PCR5 to resolve model constraints.

5.1 Transferring user constraints

Using PCR5 to transfer user constraints means that all conflicts are redistributed to elements involved in the conflict. In essence: when forcing the mass of any element to zero, that mass goes to elements at a higher hierarchical level. The first problem occurs when a high level element is constrained: where should that mass be transferred to?

Table 4 Transfers between elements of *S*.

Set to zero	Transfers to
σ_1	σ_2
$\sigma_2\,(\sigma_4, \sigma_5)$	$\sigma_1\ , \sigma_3$
σ_3	$\sigma_2\ , \sigma_5$
σ_4	σ_2
σ_5	$\sigma_2\ , \sigma_3$

This problem can be solved by proportionally transferring masses at the highest level in accordance with Table 4, which in turn is based on Figure 1. A second problem occurs because applying this rule will lead to an accumulation of masses assigned at the highest hierarchical classification level. We therefore alter the transfer concept slightly. Masses involved in a conflict are proportionally redistributed to elements at the same hierarchical level using the overlaps between the different sets parallel to how Table 4 was made. Only when no elements on the same level are left unconstrained, masses are assigned to an element on a higher hierarchical level. E.g., when the operator indicates that it is not a F16 in example 2, that mass is transferred to the F14 since they are both children of the generic fighter class.

5.2 Conflict

Constraining the subsurface domain in example 2 agrees with the information given by the two other sources: in other words the operator agrees with the system, as shown in Figure 3. When the user imposes a similar constraint on the air domain, another problem arises: the system disagrees with the operator. This conflict can be interpreted and used in three ways.

Firstly, the operator might be wrong. In this case, the conflict can be used as a alert for the operator to review the case. The conclusion can go both ways. If the operator agrees with the system this is of added training value for the operator. If the system is wrong, this instance can be used to train the automated classification algorithms.

Secondly, the conflict can be used to trigger sensor measurements. The conflict between system and operator can be traced to a single classifier that causes most of the conflict. By looking at the input of that particular classifier, we can tell which uncertainty of its input should be reduced in order to try and reduce the amount of conflict. With that information a sensor task can be generated for the sensor manager.

When conflict is not resolved by such sensor tasks, two other options must be considered. Firstly, the object is classified correctly but is behaving very unexpectedly. Secondly, a sensor system is degraded and is giving wrong measurements. Either way, the amount of conflict is used to alert the operator should this occur.

6 Implementation

The theories from the previous sections have been implemented as a part of the ongoing research in sensor management at CAMS – Force Vision. The simulation environment and the scenarios that were developed in the STATOR project have been expanded with classifiers to test the fusion of system belief and operator input. Note that the classifiers used are simple ones and will later be replaced by more intelligent classifiers that e.g. take temporal aspects into consideration. This section describes the architecture of the fusion system and the interface for classification.

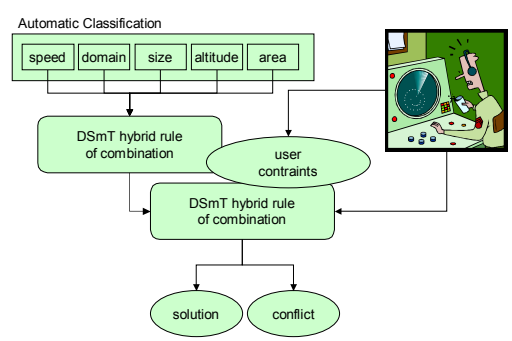

Figure 4 Basic system architecture to combine classification solutions

6.1 System architecture

In section 5.2 we saw that the user and the system interact on several levels. At the highest level, the operator defines the mission, which influences the parameters of the classifiers. This level is discarded for now since it is a component in the mission planner and not of the classification system itself. More information on this subject can be found in [15].

Two levels are left that do need to be implemented. Firstly, the level where the operator constrains the model for each individual detected (or expected) object. The second level is the operator classifying objects manually. Making this separation means that two separate combination rules must be used. The resulting system architecture is shown in Figure 4. Five different (simple) classifiers were implemented that try to classify objects based on:

1) speed;
2) domain;
3) object size;
4) altitude; and
5) area (for this classifier the mission settings define where objects are more likely to occur).

This system has two outputs. The first, of course, is the combined belief that is assigned to the various elements of the classification space. The second, the amount of conflict, is important for feedback purposes, as mentioned in section 5.2. This feedback informs the operator about decisions he makes and on how well this fits into the systems belief. The amount of conflict can be used as a trigger for the sensor manager.

6.2 Classification Interface

Besides the influence the operator has on the classification solution, it is also important for the operator to know what the current state of belief is in the system. The resulting interface, shown in Figure 5, gives the operator input possibilities and displays the current belief state of the system. In this figure, the colour indicates the amount of belief the system has in a certain element on all hierarchical levels. The operator can exclude (sets of) elements, which makes those elements transparent. The amount of conflict is also tracked. Furthermore, the user can classify an object by clicking the appropriate element. The system belief is then combined with the operator's solution using a DSmT combination rule as shown in Figure 4.

In the interface, the amount of conflict is also displayed. The amount of conflict determines the colour in which the numeric value is displayed, which alerts the operator if it increases too much. The conflict level is only determined by the constraints the operator places on the classification combination rule. When the operator classifies an object himself, the combined value to that class indicates how much the system classifiers agree with that solution; the colour intensity of that particular node also indicates that value as additional information source. This indication can prevent the operator from tunnel vision, i.e. it will emphasize contradicting evidence when the operator does not have enough time to notice that.

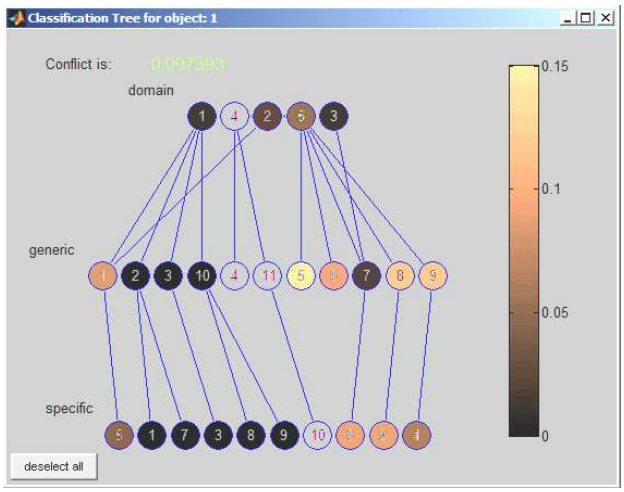

Figure 5 An interface was developed where the operator can view the system belief on the three hierarchical levels.

7 Future Work

In [3] command and control concepts and sensor management concepts were tested in a simulation environment. We will implement the classification systems discussed here in that environment. Another addition to that environment will be the implementation of the automated classifiers discussed in [15].

By expanding the implementation of the overall concepts in more complex scenarios, we will be able to conduct serious gaming tests to validate the cooperation mechanisms discussed in this paper.

Sensor management is the overall subject of ongoing study in the Royal Netherlands Navy. Mechanisms to generate sensor task requests based on the reasoning process with uncertainties need also be developed. These requests should, of course, fit into the overall sensor management concepts. As scheduling mechanism for these functions we expect to use the results from [16]. The combination will result in an overall new command and control concept.

8 Conclusions

This work shows that it is possible to use DSmT to combine operator and system belief on classification solutions. Modelling the classification space to comply with DSmT fits the real life situation in the military domain.

Operator input is very important in military applications. The interface we presented here enables an operator to exert influence on various levels in a flexible way. Furthermore, the interface gives the operator insight into the belief state of the system. The result of this insight will give the operator reason to trust the system, which leads to better cooperation still.

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